Liquefaction potential assessment using different neural and neuro-fuzzy networks: A comparative study

Evaluation de la potentielle de la liquefaction par les reseaux neurals et neuro-fuzzy: une étude comparée

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ABSTRACT: A thorough investigation on the application of neural computing methods in prediction of liquefaction potential of soils has been performed. The emphasis was on obtaining optimized neural network architecture to model the complex relationship between the seismic parameters, soil parameters, and the liquefaction potential. A Probabilistic Neural Network (PNN) with a new algorithm for adapting the smoothing variable, a Recurrent Neural Network (RNN) and a neuro-fuzzy network were employed for this investigation. Different combinations of input parameters and other network features were tried for each network. Performance of the network and its simplicity (minimum number of input parameters) were two main criteria in order to arrive at an optimum network. Results were then compared with empirical methods. The comparison indicates improvements in accuracy of the liquefaction potential assessment

RÉSUMÉ: La potentielle de la liquefaction est evaluee par les reseaux neurals et neuro-fuzzy. Le but est de trouver le reseau optimum pour ce sujet. Afin d'arriver a ce but, different types des reseaux tel que les reseaux probabilistique (PNN), recurrent (RNN), et neuro-fuzzy sont examines avec different combinaison des donnees. La comparaison montre la superiorite de cette approche.

1 INTRODUCTION

Earthquakes are one of the most destructive natural hazards. Niigata earthquake of 1964 was among the early events showing the destructive effects that may result from liquefaction of the ground. The liquefaction phenomenon may cause various adverse effects ranging from sand boils and ground displacements to loss of bearing capacity. The occurrence of liquefaction is affected by soil properties, geological conditions and ground motion characteristics.

To date, numerous investigations have been performed for determination of liquefaction potential and several assessment methods have been developed. Empirical correlations between the soil properties and seismic characteristics and the occurrence of liquefaction have been established using actual field records for liquefied or non-liquefied sites. A commonly accepted index indicating resistance of soil to liquefaction is the standard penetration test (SPT). For example, Tokimatsu & Yoshimi (1983), Seed et al. (1983), and Ambraseys (1988) have used the SPT and the cyclic stress ratio induced under an earthquake to evaluate the liquefaction potential. Berrill et al (1988) compared effective overburden pressure with the increase in pore water pressure that may result from an earthquake event to evaluate liquefaction potential. It was considered that the increase in pore water pressure is proportional to the seismic energy dissipated.

Another major approach for modeling the complex relationships of effective factors and the occurrence of liquefaction is by Artificial Intelligence methods such as neural networks or fuzzy methodologies. Works by Dou & Berrill (1993), Goh (1994) and Habibagahi & Katebi (1996), fall within this category.

Neural Networks (NN) have recently received lots of attention and contributed in a wide variety of applications in civil engineering as well as in other fields. They have been found to be useful for modeling the complex relationships involved in physical phenomena and used in place of equation-based models. A neural network is a massively parallel-distributed processor made up of simple processing units, which has a natural propensity for storing experiential knowledge and making it available for use. This paper studies the performance of various types of these networks to verify their feasibility and performance.

2 NEURAL NETWORKS

Due to the everyday growing of neural networks applications, today the concept of the neural network is widely known and can be considered a matter of general information. Therefore, in this paper the features of the networks used are described briefly.

2.1 *Back-Propagation Neural Networks (BPNN)*

These are networks of layered neurons with massive interconnections. A numerical weight is associated to each connection, which determines the nature and strength of the influence between the interconnected neurons. The weighted sum of the inputs is then transmitted through an activation function. Figure 1 shows the architecture of a typical BPNN (often called feed-forward network) composed of three layers. The input layer presents the data and the output layer holds the response of the network. It may have one or more hidden layers.

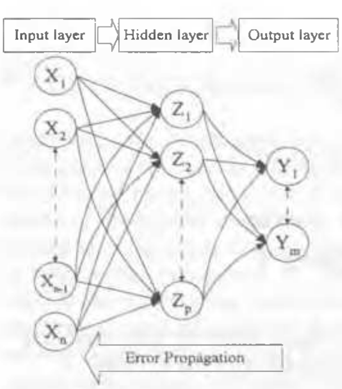

Figure 1. Typical feed-forward neural network architecture

The weights assigned to each connection are modified through a learning process in which a series of patterns composed of pairs of input and target is fed to the network. This learning process (training) tends to adjust the weight matrices of the network in order to minimize the error measure of the network, defined by:

$$E = \frac{1}{2}\sum_i [(t_i - out_i)^2] \tag{1}$$

where t_i is the target of the i[th] input pattern and out_i is the output of the network for the same input pattern

A common training algorithm is the *back-propagation* model (Rumelhart et al 1986). Back-propagation is an iterative algorithm that uses a gradient descent method to calculate the changes in the weights and ultimately to reduce the error to an acceptable value. Weight updates may be performed each time an input is presented to the network *(online method)* or the error may be averaged and weights changed over all input patterns *(batch method)*. Details of the back-propagation method can be found in the related publications.

2.2 *Recurrent Neural Networks (RNN)*

These networks are fundamentally very similar to the feed-forward networks. It is now recognized that RNNs are usually superior to other kinds of networks in learning sequential (or time varying) patterns since their hidden nodes can transmit their outputs to both input and output layers simultaneously (Zhu, et al 1998). In this study, a simple recurrent net was used, which can be considered, as a "partially recurrent" net in which, only the outputs from hidden neurons were fed-back to the input layer. The process of training a recurrent network is identical to what was discussed previously for feed-forward networks with back-propagation of errors (BPNN).

2.3 *Probabilistic Neural Networks (PNN)*

The probabilistic neural net is constructed using ideas from classical probability theory, such as Bayesian classification, and classical estimators for probability density functions, to form a neural network for pattern classification. Compared with back-propagation, PNN offers major advantages such as rapid training, easy data add or remit, and guaranteed convergence. The PNN is a direct outgrowth of earlier works with Bayesian classifiers. Bayesian classification requires a pdf (probability density function) for each class. Parzen (1962) developed such a technique to estimate the pdf from sparse, real-world data sets, which are commonly called the method of Parzen windows. A unit area Gaussian curve (basis function) is drawn for each sample in the training set (in that class) centered at the value of the feature. All of the curves are then added to produce the composite curve. Parzen showed that with a large number of samples and suitable scaling, the composite curve approaches the true pdf. The multi-category classifier may be expressed as follows (Wasserman, 1993):

$$D(\mathbf{X}) = \Theta_r \Leftrightarrow \sum_{i=1}^{n} h_i^r \geq \sum_{i=1}^{m} h_i^s \tag{2}$$

$$h_i^r = \exp[-(\mathbf{X} - \mathbf{Y}_i^r)^T(\mathbf{X} - \mathbf{Y}_i^r)/2\sigma^2] \tag{3}$$

for all classes of r not equal to s, where

D(**X**) = the decision on test vector **X**
Θ_r = Class r
X = Test vector
$\mathbf{Y}_i^r$ = i[th] training vector of class r (center of basis function)
n, *m* = training vectors in classes r and s respectively

PNN is a network representation of this approach, shown in Figure 2.

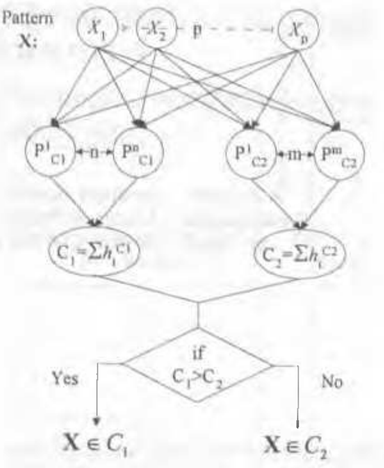

Figure 2. Block diagram for PNN (with two class decision making)

2.3.1 *Training the pdf Shapes*

It is possible to improve accuracy by adjusting the shape of the basis function. This may be accomplished by generalizing the exponential function of equation (3) to the following:

$$h_i^r = \exp[-(\mathbf{X} - \mathbf{Y}_i^r)^T \mathbf{K}(\mathbf{X} - \mathbf{Y}_i^r)/2] \tag{4}$$

where **K** = the inverse of the covariance matrix of the input vectors

2.4 *Adaptive Network-based Fuzzy Inference System (ANFIS)*

ANFIS is a fuzzy inference system employing fuzzy *if-then* rules proposed by Jang (1993). It can model the qualitative aspects of human knowledge and reasoning processes without employing precise quantitative analyses. ANFIS can serve as a basis for constructing a set of fuzzy if-then rules with appropriate membership functions to generate the stipulated input-output membership functions. The network is composed of five layers as shown in Figure 3. Each layer performs a certain task as described below:

Layer 1: The nodes in this layer represent the fuzzy sets assigned to each input variable. A bell-shaped membership function is often used. The output of this layer is the membership functions evaluated for a set of input variables. This layer contains unknown parameters defining spread, center and shape of the membership functions.

Layer 2: In this layer each node performs a multiplication of the input signals and outputs the product to the next layer. The number of nodes in this layer represents the number of fuzzy rules available in the network and the outputs, w_i, represent the firing strength of the pertinent rules.

Layer 3: Each node in this layer determines the normalized firing strength of each rule determined by:

$$\overline{w}_i = w_i \Big/ \sum_{j=1}^{N} w_j \tag{5}$$

where N = number of fuzzy rules available in the network

Layer 4: The output of this layer is the product of the normalized firing strength and a function *f*, which is a linear combination of the input variables plus a constant term, expressed by:

$$O_i^4 = \overline{w}_i f_i = \overline{w}_i(p_i X_1 + q_i X_2 + r_i) \tag{6}$$

where p_i, q_i and r_i = unknown parameters of this layer to be determined by training the network.

Layer 5: The output layer with one node simply sums all the inputs from the previous layer

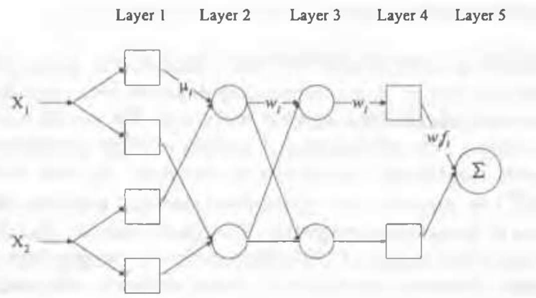

Figure 3. Typical ANFIS architecture

Table 1. Results for the selected networks

Network	Parameter Combination	Network Type	h_n*	Success Rate Train	Test	Overall (%)
1	M, N_1^{60}, a_{max}, σ_0, σ'_0, D_{50}	BPNN	4	94/105	25/29	88.8
2	M, N_1^{60}, a_{max}, σ'_0, D_{50}, F_C	BPNN	5	100/105	25/29	93.3
3	M, N_1^{60}, σ_0, σ'_0, D_{50}, F_C, R_f	BPNN	8	55/55	10/11	98.5
4	M, N_1^{60}, σ_0, σ'_0, D_{50}, F_C, R_e	RNN	5	62/62	15/16	98.7
5	M, N_1^{60}, R_e	BPNN	2	72/79	19/20	91.9
6	M, N_1^{60}, R_e	PNN	-	73/79	15/20	88.9
7	M, N_1^{60}, R_e	ANFIS	-	79/79	18/20	97.8

*h_n = Number of neurons in hidden layer

3 DATABASE PROCESSING

The accuracy and performance of a neural model for any phenomena is severely affected by the database on which its learning phase had been based. Firstly, a good understanding of the physical phenomena is required to make use of relevant parameters in building the model. Secondly, it is very important to take care of the consistency and reliability of records when they are obtained from different sources. In this study, a total number of 188 records of liquefied or non-liquefied case histories from various earthquakes around the world were employed to prepare the necessary database. The records were compiled from works reported by Davis & Berrill (1982), Ambraseys (1988), Haeri (1991), Bartlett & Youd (1992), and Christensen (1995). Unfortunately, not all of the 169 records contained full information of all the effective parameters. Most of the records were lacking R_e or R_f while some suffered from inexact values for D_{50} or F_C.

4 NEURAL NETWORK ANALYSIS

As described before, four different types of neural networks of BPNN, RNN, PNN, and ANFIS were utilized for the present study. These networks with 11 combinations of input parameters were used to study the liquefaction potential. Each of the four neural network types was examined using the above-mentioned combinations. For BPNN (Back-Propagation) and RNN (Recurrent Neural Network), various numbers of neurons for the hidden layer were tried in order to achieve the best performance for the network. The networks with higher performances or lower complexity (i.e. lesser number of input parameters and hidden neurons) were chosen for further study. These networks are shown in Table 1.

With increasing number of input parameters distinct improvements in the performance of the networks were noticed, however, due to the high complexity of these networks and the limited number of records available, simple networks with minimal number of input parameters and having acceptable success rates were selected for further studies (networks #5, #6 and #7 in Table 1).

Table 2. Weights for network #5

Hidden Neurons	Connection Weights M	N_1^{60}	R_e	Output
1	-0.455	-1.265	-12.94	16.79
2	16.536	-17.91	-4.31	8.755
bias	-	-	-	-6.55
Relative Importance (%)	22.9	27.4	49.7	-

Table 3. The empirical methods performance

Method	Rate of Success (%)
Tokimatsu & Yoshimi	77.5
Seed et al.	77.2
Berrill et al	86.9
Ambraseys	81.2

Table 2 presents the weights for the network #5 together with the relative importance of various input parameters determined using the algorithm proposed by Garson (1991). From this Table, it may be concluded that the epicentral distance has the highest importance compared to other input parameters.

5 PARAMETRIC STUDY

In this section, the liquefaction potential is evaluated from results obtained from networks #5, #6 and #7 of Table 1. Figures 4, 5 and 6 indicate the boundary curves separating liquefiable and non-liquefiable zones for networks #5, #6 and #7 respectively. All graphs of Figures 4, 5 and 6 indicate that the SPT-*N* values separating liquefaction and non-liquefaction zones increase with a decrease in the epicentral distance. The figures also indicate that for low SPT-*N* values, the epicentral distance on the separating curves is only a function of the earthquake magnitude. These upper bounds of epicentral distance for liquefaction, shown in Figure 5 are relatively consistent with the empirical the equation proposed by Ambraseys (1988).

6 COMPARISON WITH PREVIOUS WORKS

Conventional methods available were used to predict liquefaction potential for records compiled in the database in order to compare their performance with that of neural networks. These methods include approaches proposed by Tokimatsu & Yoshimi (1983), Seed et al (1983), Berrill et al (1988), and Ambraseys (1988). The success rates of the above-mentioned methods are presented in Table 3.

It should be mentioned that the function C(N), used in the equation proposed by Berrill et al (1988), was recomputed using the current database. Comparison of these results with Table 1 indcates advantage of AI methods over conventional approaches.

7 SAFETY FACTOR EVALUATION

Safety factor for liquefaction has been traditionally been defined as the ratio of the resisting cyclic stress ratio to the cyclic stress ratio induced by seismic event. It is known that in constant conditions of earthquake magnitude, depth and soil properties; the developed cyclic stress ratio is proportional to the peak horizontal acceleration (Tokimatsu & Yoshimi, 1983). Thus, we may redefine the liquefaction safety factor as the ratio of horizontal acceleration required to liquefy a given soil (an index of soil resistance to liquefaction) to the maximum horizontal acceleration experienced from an earthquake. In other words:

$$S.F = \frac{(a)_{LIQUEFACTION}}{(a_{max})_{EARTHQUAKE}} \quad (7)$$

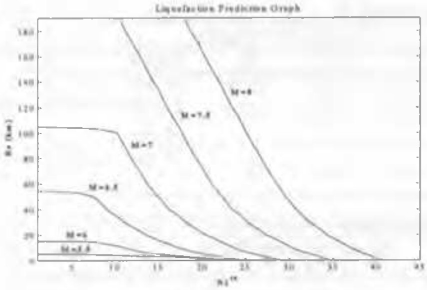

Figure 4. Prediction curves for network #5 (lower-left zones of each curve represents liquefaction)

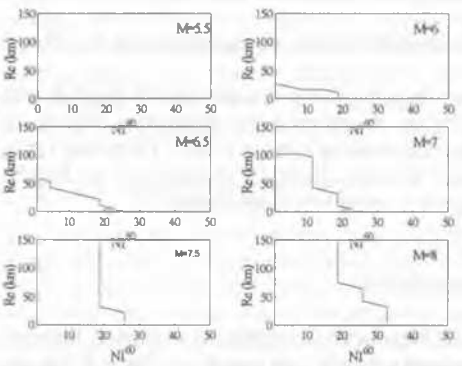

Figure 5. Prediction curves for network #6 (lower-left zones of each curve represents liquefaction)

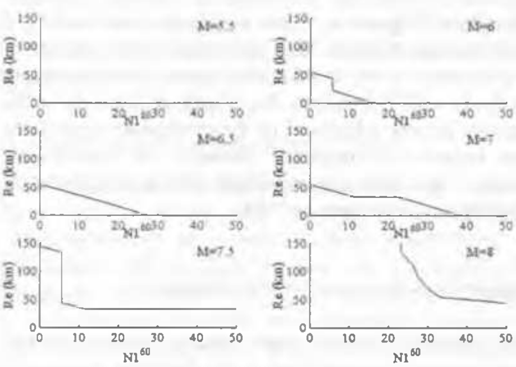

Figure 6. Prediction curves for network #7 (lower left zones of each curve represents liquefaction)

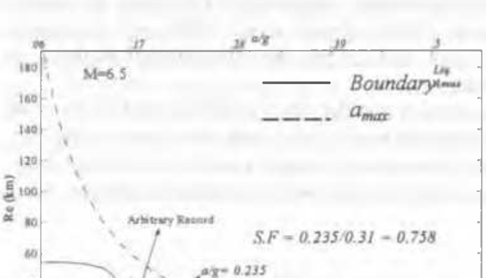

Figure 7. Example for the calculation of the safety factor

An appropriate attenuation law is then required to calculate acceleration values versus epicentral distance to be used in conjunction with the liquefaction prediction graphs presented in Figures 4, 5 and 6. The following equation is proposed for the correlation between R_e and a.

$$a_{max}=1.3328e^{0.2546M}(19.77+R_e)^{-0.8456} \quad (8)$$

An example of the safety factor computation is illustrated in Figure 7.

8 CONCLUSION

In this paper, several types of NN were employed to assess the liquefaction potential. A comprehensive database was compiled from available records from all over the world. NN results indicate that simple NN with a minimal number of input parameters (earthquake magnitude, M, epicentral distance, R_e, and SPT value, N_1^{60}) is superior to conventional methods available for evaluation of liquefaction potential. The results indicate that the farthest epicentral distance to liquefaction sites is independent of SPT values. However, this critical R_e value increases with earthquake magnitude. Furthermore, a simple procedure was proposed to evaluate the safety factor against liquefaction for a given site and a given earthquake.

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